

Optimizing Checkpoints for Arrival Time Prediction

Johannes Asamer*, Anita Graser, and Matthias Prandtstetter
AIT Austrian Institute of Technology, Department Mobility, Vienna, Austria, johannes.asamer@ait.ac.at

Mario Ruthmair
University of Vienna, Department of Statistics and Operations Research, Vienna, Austria, mario.ruthmair@univie.ac.at

Extended Abstract

To improve processes at freight trans-shipment centers (FTSCs), it is essential to know when vehicles will arrive in order to schedule and coordinate activities and to optimally employ manpower and machines. Therefore, in this study we describe the optimization of checkpoint locations in order to accurately estimate the arrival of approaching vehicles. In multi-modal FTSCs arrival time estimation is performed differently for each mode of transport. For example, travel times on inland waterways are mainly determined by properties of the ship (e.g., width or draught) which can be used to predict arrival time at the harbour (cf. [1]).

In contrast, arrival times for road vehicles may be estimated from various sources providing travel times (e.g., Google Maps). However, these systems mostly aim at predicting travel times of passenger cars and are not suitable for trucks because of different speed limits. Moreover, to estimate arrival times it is mandatory to know the location of the truck on its way to the FTSC. If the vehicle is equipped with GPS and positions are transmitted to an operator, the travel time to the FTSC can be continuously estimated. However, if such a system is not available to the operator of an FTSC, a solution could be to automatically detect trucks at checkpoints along the road and subsequently estimate arrival times. For this purpose an automatic number plate recognition (ANPR) system may be used, which allows to reliably detect trucks according to their number plate (cf. [2]). Since ANPR systems are cost intensive only a limited number of devices can be installed.

In order to optimize the planning abilities in the FTSC, the objective of this work is to formulate and solve a multi-objective optimization problem to find checkpoint locations for trucks with the following (partly contradicting) objectives:

- Minimize the number of checkpoints
- Maximize the average residual travel time from checkpoint to FTSC
- Maximize the average certainty of residual travel times

As a side constraint a given minimal detection rate of approaching trucks has to be satisfied. The detection rate is defined as the ratio between the sum of all detected trucks at the checkpoints and the total number of trucks heading for the FTSC. The certainty of residual travel times is based on the buffer time index (BTI, cf. [5]), which is the ratio between average delay and expected travel time. The BTI is positive and unlimited with low values representing a high certainty in travel time. The certainty of the BTI itself depends on the number of underlying travel time observations. Therefore, we combine the BTI and the number of observations and scale it to the interval $[0,1]$. We call this indicator 'quality' with 1 as best and 0 as worst possible value. The average travel time from a checkpoint to the destination (FTSC) is estimated from historic truck data.

The goal is to find a minimal number of checkpoints to detect trucks, from which the average residual travel time to the FTSC and the corresponding average quality is maximal. Each link of the underlying road network is a potential checkpoint location.

The optimization problem is modeled as a mixed integer linear program [4], applied to truck movement data, and solved using the CPLEX framework embedded in a variant of the epsilon-constraint method [3]. We use binary variables to indicate if a link of the road network is selected for a checkpoint. Although a trip can pass several checkpoints it accounts only once to the sum of detected trips. It can be easily seen that the three types of objectives and the constraint are partially contradicting, so we consider a tri-objective

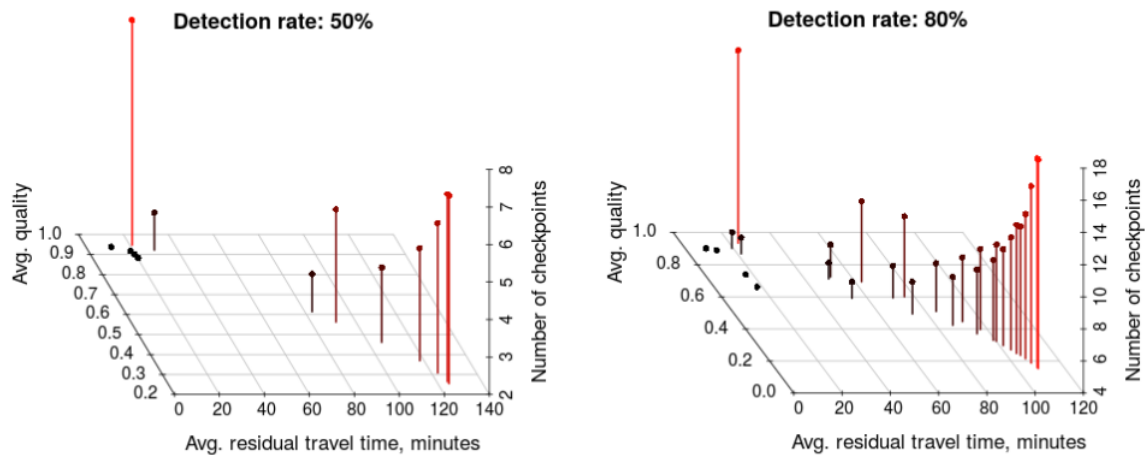


Figure 1: Pareto-optimal solutions for 50% (left) and 80% (right) detection rate. The color gradient from black (low) to red (high) refers to the number of checkpoints.

optimization approach to obtain a set of pareto-optimal solutions which can be handed over to the decision maker (cf. Figure 1).

Figure 1 shows that average residual travel time can be mainly increased if a lower quality is accepted and vice versa. Trucks come from several sources in the surrounding area and use a variety of different roads on their way to the FTSC. As they approach their destination, residual travel time decreases as well as the number of possible road links to use. This results in a lower number of checkpoints to be installed in order to achieve the same detection rate. It can be easily seen in the figure that an increased number of checkpoints corresponds to an increased average residual travel time. This relation is not obvious with respect to average quality and number of checkpoints. In Figure 1 we can also see that for a certain range of average residual travel time (left plot: 30-80 minutes, right plot: 20-50 minutes) no pareto-optimal solution exists, which is due to peculiarities of the investigated road network. The solutions with a very low number of checkpoints (approximately two in the left plot and four in the right plot in Figure 1) exhibit a small average residual travel time and very high average quality (≈ 0.9). However, the highest average quality slightly above 0.9 is only achievable with a large number of checkpoints. This indicates that the number of checkpoints is rather sensitive to average quality and a high average quality will most probably result in a costly solution. In other words, large amounts of installation costs can be saved if small reductions in average quality are accepted.

Based on the presentation of the pareto-optimal front a decision maker can choose a preferred setting e.g., based on carefully weighting the gain of increasing average residual travel time against the resulting loss in average prediction quality or deciding if additional checkpoints should be used to increase quality or residual travel time.

References

- [1] J. Asamer and M. Prandtstetter. Estimating ship travel times on inland waterways. In *TRB 93rd Annual Meeting Compendium of Papers*, 2014.
- [2] M. Friedrich, P. Jehlicka, and J. Schlaich. Automatic number plate recognition for the observance of travel behavior. In *8th International Conference on Survey Methods in Transport: Harmonisation and Data Comparability*, 2008.
- [3] G. Mavrotas. Effective implementation of the ε -constraint method in multi-objective mathematical programming problems. *Applied Mathematics and Computation*, 213(2):455–465, 2009.
- [4] G. L. Nemhauser and L. A. Wolsey. *Integer and combinatorial optimization*. Wiley-Interscience, 1988.
- [5] J. Van Lint, H. J. Van Zuylen, and H. Tu. Travel time unreliability on freeways: Why measures based on variance tell only half the story. *Transportation Research Part A: Policy and Practice*, 42(1):258–277, 2008.